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Biologically-Based Neural Network Model of Color Constancy and Color Contrast

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ABSTRACT

The light which reaches the eye, or any other sensor, is the product of the reflectance and the illuminant. Therefore, in order to determine the surface reflectance of an object independent of the illuminant, a system must use the spatiochromatic context of the image. We have developed a neural network based on the anatomy and physiology of the visual projection from retina to V4. The network combines color-opponent and contrast information to achieve a good degree of color constancy. This network has been tested on simulated images corresponding to the stimuli used in well established psychophysical experiments. Responses qualitatively match human responses to a variety of center-surround and Mondrian test stimuli.

INTRODUCTION:

Color constancy is the ability to maintain an approximately constant color perception despite changes in the incident illumination of the object. Color contrast, also referred to as chromatic induction or simultaneous contrast, is the change in the (perceived) color of a surface due to the spectral composition of neighboring surfaces. Color perception in natural scenes depends upon both of these phenomena. Together, these two effects demonstrate that color perception does not directly depend upon the wavelength of the light reflected from a surface.

Many theories for color constancy and color contrast have been proposed previously (e.g. D'Zmura and Lennie, 1986; Maloney and Wandell, 1986). However, they usually have required unrealistic assumptions about images, had only loose connection to anatomy and physiology, or required that parameters be changed for each image. The dependence of color constancy and color contrast on the spatiochromatic properties of a large portion of the image (e.g. Walraven, 1976; Blackwell and Buchsbaum, 1988a,b; review by Jameson and Hurvich, 1989) suggests that a distributed method of processing, such as that provided by neural networks, could be very useful in solving this problem.

Several neural network models have been proposed. For example, Grossberg (1987) proposed a model in which color information is obtained from the contrast at boundaries and then the color is filled into each segment of the image. Dufort and Lumsden (1991) used double-opponent cells as a mechanism for color constancy. Usui, Nakauchi, and Miyake (1990) developed a neural network which transformed color signals from cone signals to the very narrowly tuned color responses which Zeki (1980, 1983) reported finding in V4. They trained this network using back-propagation and found that the hidden units resembled the color opponent cells in the retina and LGN.

One of the best known algorithms for color constancy, Land's retinex algorithm (Land 1964, 1986), calculates the relative "lightness" of each area of a scene within three separate channels, each sensitive to a different region of the visual spectrum. Moore, Allman, and Goodman (1991) implemented the retinex algorithm within a network structure. One limitation of the retinex is that the interiors of large uniform regions become gray. Moore *et al.* (1991) incorporated a modification in order to eliminate this washout problem by multiplying the surround factor by the "edginess" of the area. Hurlbert and Poggio (1988) demonstrated that, using a number of different "learning" methods, including least squares gradient descent and back propagation in neural networks, a linear operator could be found which is similar to that proposed in the retinex algorithm.

One of the most fundamental problems with many of these networks is that because they record only contrast, they require assumptions about the average to which that contrast refers. A common assumption made is the "gray world" assumption, which states that the average chromaticity is constant for all images. This was developed formally by Buchsbaum (1980) and has been used in many color constancy algorithms since. Other assumptions include that the brightest spot in an image is white, or that the illumination varies slowly in space.

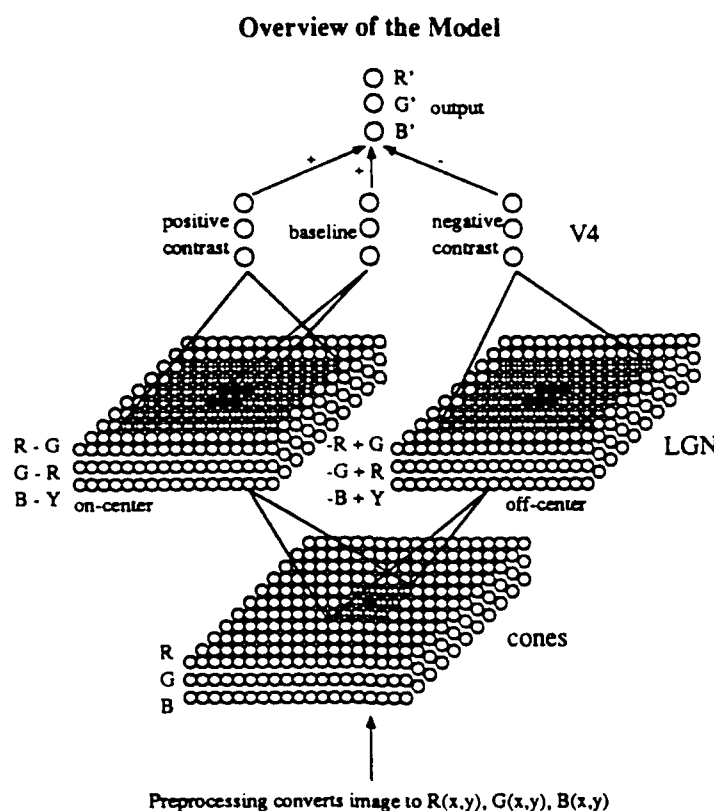
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while reflectances have sharp chromatic borders. These assumptions hold for many scenes, but when they do not hold these algorithms can make predictions far from the psychophysical results. In the following section, we describe how our model eliminates both the washout problem and the need for assumptions about the scene by measuring the baseline as well as the contrast.

THE MODEL:

We have developed and simulated a neural network model that provides a biologically plausible neural architecture capable of producing color constancy and color contrast. The model is based on primate anatomical and physiological data from the retina to V4 and incorporates both classical center-surround inhibition as is found in the retina and LGN, and the extremely wide-field "silent surround" inhibition reported in V4 (Schein and Desimone, 1990). As is shown in figure 1, the simulation includes a preprocessor which converts an image from either CIE coordinates or Munsell notation to the cone activities: $R(x,y)$, $G(x,y)$, $B(x,y)$. These three matrices of activation levels comprise the input to the network.



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Figure 1: Overview of the network model showing connection patterns at each stage. See text for details.

The input is then fed to a center-surround color opponent stage. Each of the three color pathways consists of an on-center and an off-center pathway whose receptive fields are defined by a difference of Gaussians. The center receives input from a single cone. The surround receives input from multiple cone types. The center and surround are sensitive to different wavelengths and so are called color opponent. The center-surround stage provides the input for the large "silent surround" stage which is based on the physiological results of Schein and Desimone (1990) and Zeki (1980, 1983) from area V4 in the macaque cortex. Each of these units has a large (up to 16°) surround outside of its classical receptive field which is tuned to approximately the same wavelength as its center, unlike the color opponent cells in the previous layer. The connection strength of the inputs to these surrounds decreases with increasing distance from the center.

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We refer to these units with large surrounds as contrast cells. We define "positive contrast" as the center being more active than the surround and "negative contrast" as the surround being more active than the center. Positive contrast cells receive input from on-center cells and negative contrast cells receive input from off-center cells. However, if the network measured only contrast, it would require the gray world assumption, as many of the previous models did. Therefore, this network model calculates the "baseline" level as well as the contrast.

The "baseline" is a local average of the color opponent response. This is consistent with the physiological results of Schein and Desimone (1990) who found that, while most of the cells in V4 did have silent surrounds, there was also a significant quantity that did not have these surrounds. Therefore the baseline is calculated by units based on the classical receptive fields of V4 cells.

Figure 2 shows how the contrast and baseline information are combined in this model to create a single representation of "color". In the case where both positive and negative contrast are zero (i.e. the case of a large uniform field) the output should follow the baseline cells. This avoids the washout problem. However, if the surround response is less than the center (positive contrast) the output is enhanced above the base activity, whereas if the surround response is more than the center (negative contrast) then the output is reduced below the base activity. This follows the psychophysical result that a gray square looks darker against a bright background than against a dark background. This calculation is done separately in each of the color channels. As is shown in figure 1, the contrast and baseline calculations are done only for the center of the input image for simplicity and minimized run-time.

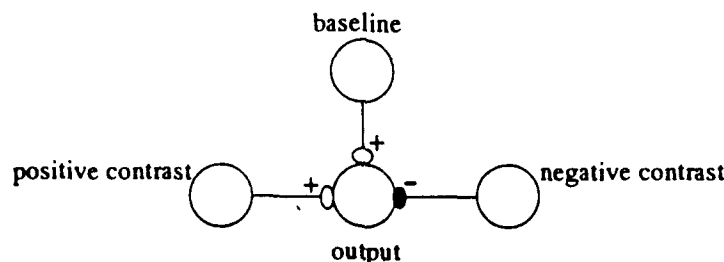


Figure 2: The output for each color channel is the baseline response plus the difference between the positive and negative contrasts. See figure 1.

THE SIMULATION:

The network was simulated using NEXUS, a biologically based neural network simulation program written at the University of Pennsylvania by Paul Sajda and Leif Finkel (1992). NEXUS is designed for creating multiple, large-scale neural maps and provides considerable flexibility in assigning physiological properties and anatomical architectures. The program is written in C and features a graphical user interface (X-window based) which makes setting up networks straightforward. Any network variable can be monitored in display windows, and a number of diagnostic tools are available.

The simulation was tested for color contrast response using center-surround images with varying separation between the center and the surround. Blackwell and Buchsbaum (1988a) have shown that the size of the color shift decreases as the distance between center and surround increases. As is shown in figure 3, the network simulation also shows this behavior. This is a consequence of the weighting function of the silent surrounds in the V4 stage of the model.

The simulation was also tested for its color constancy ability using the classical McCann Mondrian demonstration (McCann, McKee, and Taylor, 1976) in which the illuminant on one Mondrian image is changed until the physical R,G,B of a patch in that Mondrian is identical to a patch with different reflectance in a Mondrian under a white illuminant. The particular case that we used was to change the illuminant on one Mondrian so that a colored patch had the same physical, input R,G,B as a gray patch in the Mondrian under the white illuminant. A human presented with this situation is able to distinguish the colored patch from the gray patch. We simulated this experiment with the network using several different colored patches. As is shown in figure 4, the network is able to distinguish the colored patch from the gray patch. In addition, the outputs are similar (but not identical) for the same patch viewed under the two different illuminants. (Note that human color constancy is not 100% effective either.) Thus the network demonstrates the major properties of human color constancy.

Test for Spatial Properties of Color Contrast Response

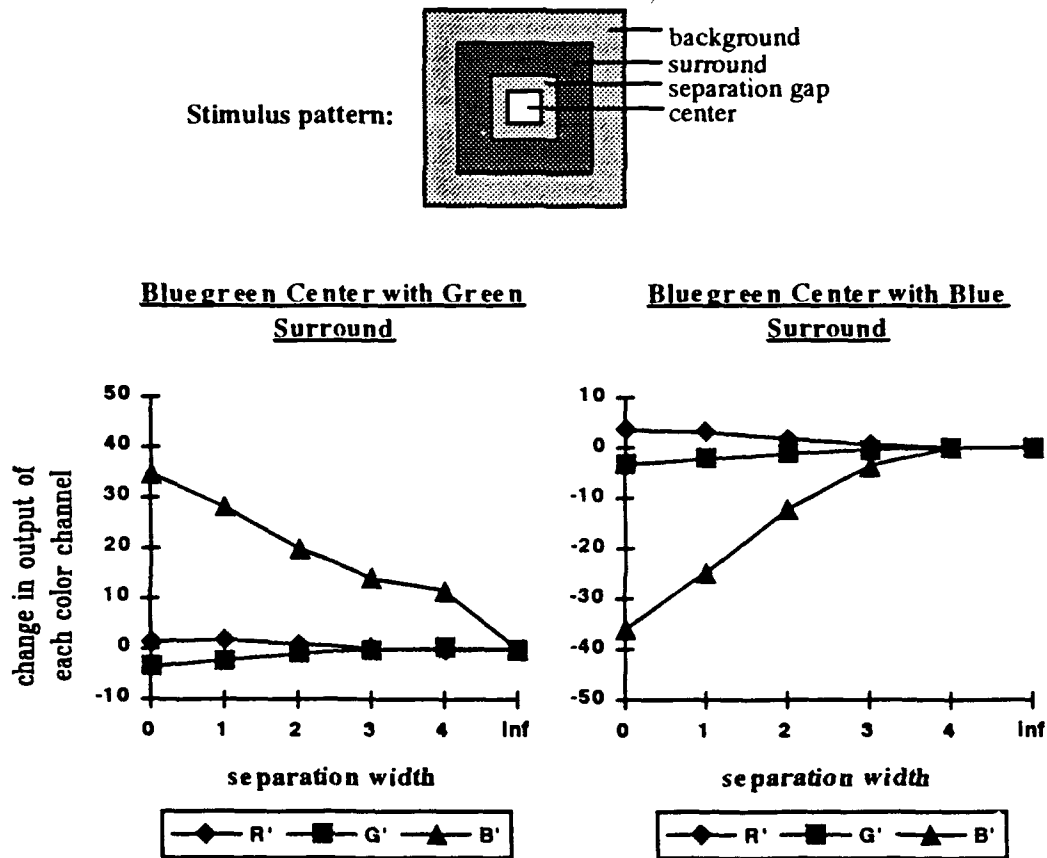
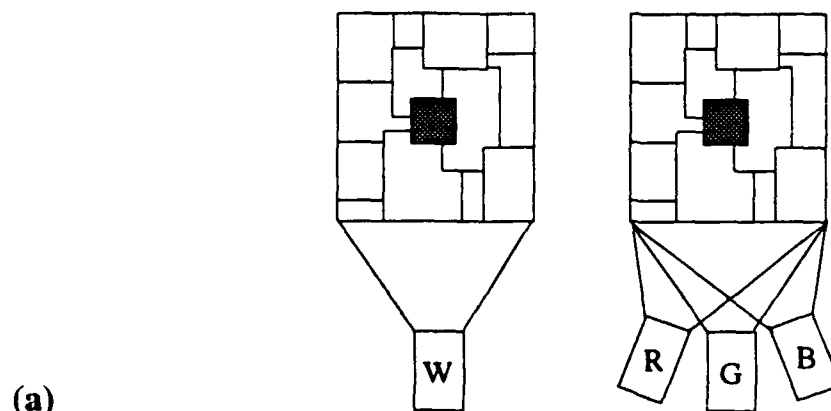
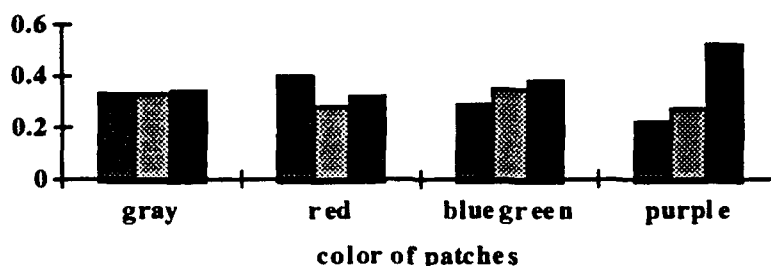


Figure 3: Change in output of each color channel for a bluegreen patch due to a green surround and a blue surround. The change is defined as the difference between the outputs with and without the indicated surround.

McCann Color Constancy Experiment Simulation



Relative Outputs of Color Channels



(b)

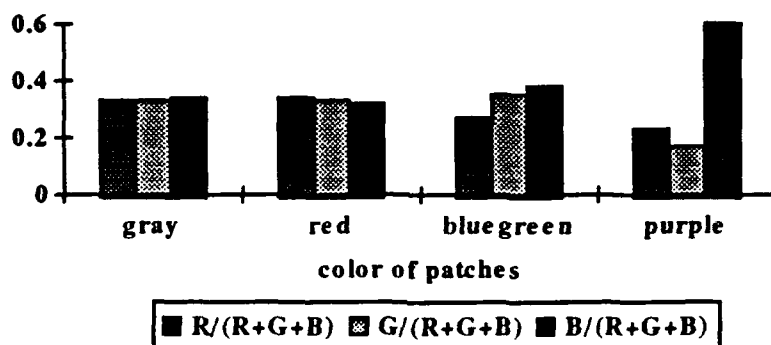


Figure 4: (a, previous page) The experimental setup. The left Mondrian has a gray patch in the center and a constant white illuminant. The right Mondrian has a test patch in the center which may be any color. The intensities of the three colored lights on the right Mondrian are changed until a light meter registers the same cone R,G,B for the test patch as for the gray patch. (b) The normalized output of the simulation's three color channels in V4 to patches of different reflectances within a simulated Mondrian. The top set of data for each colored patch is the output under a white illuminant. The bottom set of data is the output under an illuminant which gives each patch the same input R,G,B as the gray patch under the white illuminant. Therefore, if there were no color constancy effect, the outputs in the bottom graph (altered illuminant) would all be identical to the output for gray.

Conclusion:

We have developed a neural network model of color constancy and color contrast which agrees with the psychophysical data. Because it uses multiple cell types to retain information about the baseline at each point as well as the contrast, it requires no assumptions about the properties of images and does not suffer from the wash-out problem that the retinex algorithm has. Because the network is based closely on components of the visual system, it may be used to test hypotheses about the relative significance of these components to the human color constancy abilities. There has been much debate over the relative significance of cone adaptation versus cortical processing in color perception. We can now add adaptation to the network and compare its contribution to that of the V4 stage. Each parameter (e.g. the size and shape of each receptive field, relative connection strengths of the base, the positive, and the negative contrast cells to the output) may be manipulated separately and the output monitored.

We would like to incorporate two additional features into this network. The network does not currently use any learning algorithms. All parameters are taken from physiological data. However, we believe that the large receptive fields of the contrast cells could be developed through a Hebbian learning process. Also, this network would be more useful as an artificial color recognition device if the output were immediately interpretable as a defined color, rather than as an activity pattern in a population of cells. Therefore, we will add a parallel-distributed-processing network to the biologically based network to act as a pattern recognition device. The PDP will be trained on images of single color patches on gray backgrounds under a standard, achromatic illuminant. Therefore, the changes in predicted color appearance under other illuminants and using other back-

grounds will be due to the biological network, not the PDP.

Our results so far indicate that the contrast within each color channel (as is apparently measured in V4 of the visual cortex) is the most important parameter affecting color constancy and color contrast. This model addresses how the contrast is used and what other information is needed.

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